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SPATIOTEMPORAL OVIPOSITION AND HABITAT PREFERENCES OF *OCHLEROTATUS TRISERIATUS* AND *AEDES ALBOPICTUS* IN AN EMERGING FOCUS OF LA CROSSE VIRUS[1]

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ABSTRACT. The number of cases of encephalitis caused by La Crosse virus recently has increased in southwestern Virginia counties. This article presents results of a study conducted from May to September 2000 in Wise County, VA, that examined the area-wide oviposition activity and habitat preferences of *Ochlerotatus triseriatus* and *Aedes albopictus,* potential vectors of La Crosse virus in the region. Data from 490 ovitrap collections made throughout the county showed that mean oviposition activity throughout the study was higher for *Oc. triseriatus* (20.4 eggs/trap-day) than for *Ae. albopictus* (3.7 eggs/trap-day). The 2 species also had distinct habitat preferences for oviposition, with *Oc. triseriatus* favoring forested habitats and *Ae. albopictus* favoring urban/residential habitats. A landcover map of 6 habitat types derived from Landsat satellite imagery of the county showed that 63% of the county was forested and 18% was urban/residential. A Bayesian decision-rule model that incorporated the ovitrap data and landcover map was moderately successful at predicting the occurrence of high oviposition activity and abundance of the 2 species. The predictions reflected seasonal and spatial fluctuations in oviposition activity, with accuracies between 55 and 79% for *Oc. triseriatus* and 70 and 94% for *Ae. albopictus.* Kappa (K), a measure of the predictive power of the model, varied from poor ($K < 0.4$) to good ($0.4 < K < 0.75$) for both species, and was highest during periods when actual egg abundance was high. This suggests that the predictions were most accurate during periods when the risk for La Crosse virus transmission is greatest. Limitations and suggestions for improving the model are discussed.

KEY WORDS *Aedes albopictus, Ochlerotatus triseriatus,* La Crosse virus, oviposition, remote sensing, Bayesian modeling

INTRODUCTION

The mosquito species *Ochlerotatus triseriatus* (Say) is a known vector of La Crosse virus (LAC, Bunyaviridae: California serogroup) (Sudia et al. 1971; Watts et al. 1972, 1973a), which causes La Crosse encephalitis, the most prevalent pediatric mosquito-borne disease in the USA during most years. *Aedes albopictus* (Skuse) also is a potential accessory vector in the LAC cycle (Grimstad et al. 1989, Gerhardt et al. 2001). Recently, there has been an increase in the number of cases of La Crosse encephalitis in southwestern Virginia. During the 5-year period from 1994 to 1998, a total of 13 cases were recorded in 4 counties in the Appalachian Mountains of Virginia (Fig. 1); 1 case was recorded in the entire state during the 19 years prior to this period. In 1997 alone, 5 confirmed cases of La Crosse encephalitis were reported in Wise County, VA, constituting a rate of approximately 13 cases/100,000.

Case site studies suggest that populations of *Oc. triseriatus* and *Ae. albopictus* may occur throughout southwestern Virginia and that their abundance, as measured by oviposition, varies with habitat type. For example, at a La Crosse encephalitis human case site, *Ae. albopictus* was found to oviposit preferentially in the yard surrounding the home, while *Oc. triseriatus* showed no preference, ovipositing equally in the yard and adjacent forests (Barker et al. 2003). In a nearby area of West Virginia endemic for LAC, Nasci et al. (2000) found that the *Oc. triseriatus* population densities were related to habitat type, with higher densities occurring in mixed northern hardwood habitats, containing primarily large maples than in sites with hemlocks mixed with hardwoods or in an abandoned orchard site containing a large number of small maple trees. While local case studies on mosquito-habitat associations will continue to provide useful information for evaluating disease risk, modern ecologically based pest-management tenets suggest that it is equally important to recognize that the local occurrences of pests usually are related to their presence over a larger geographic area (National Research Council 1996). Therefore, for insects such as mosquitoes that utilize human beings and other vertebrates as hosts, there is a need also to develop an understanding of the spatial interactions among the insect, its breeding habitats, and host populations over broader geographic areas.

Because populations of *Oc. triseriatus* and *Ae. albopictus* are associated with characteristic habitats, geospatial approaches such as remote sensing,

[1] An abbreviated description of this research was published previously in the Proceedings and Papers of the 70th Annual Conference of the Mosquito and Vector Control Association of California (Barker et al. 2002).

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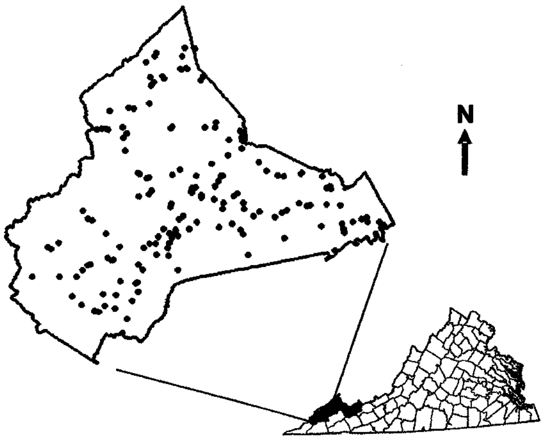

Fig. 1. Counties in southwestern Virginia (shaded) reporting cases of La Crosse encephalitis between 1994 and 1998. Wise County (enlarged) showing the distribution of ovitrap collection sites.

geographic information systems, and spatial surveys and modeling can be used to study regional landscapes and to identify preferred breeding habitats for these species. Other studies already have shown that geospatial technologies can be used to assess the relationships between environmental and habitat variables and disease vector abundance (e.g., Rogers and Randolph 1991, Wood et al. 1992, Beck et al. 1994, Cross et al. 1996, Roberts et al. 1996, Baylis et al. 1998, Moncayo et al. 2000).

The objective of this study was to characterize ovipositional habitat preferences of *Oc. triseriatus* and *Ae. albopictus* in Wise County, VA, where La Crosse encephalitis has emerged recently. Data from geographically referenced ovitrap collections in various habitat types then were combined with remotely sensed satellite data to develop a Bayesian decision-rule model to classify Wise County into probabilities of high oviposition activity for *Oc. triseriatus* and *Ae. albopictus*.

MATERIALS AND METHODS

Study area

The study was conducted in Wise County, VA (36°44′ and 37°14′N, and 82°14′ and 82°54′W), in the southern Appalachian Mountains (Fig. 1). Wise County is ~1,072 km² and the landscape is dominated by mixed hardwood forests, including oak–hickory, maple–beech–birch, and white pine–hemlock forest types (Johnson 1992). Small towns, barren land cleared by coal mining, and occasional pastureland are interspersed among the forest stands. Elevation within the county ranges from ~400 to 1,287 m, with most populated areas located at elevations between 400 and 800 m. Average annual precipitation recorded at the Wise 3 E weather station in Wise, VA, is 119 cm, and the average temperatures in January and July are 0 and 22°C, respectively (National Oceanic and Atmospheric Administration 2003).

For this study, areas within the county were categorized into 6 broad landcover types or habitats (forest, urban/residential, shrub and brush rangeland, herbaceous rangeland, barren land, and water) based on knowledge of the landscape and the land use and landcover scheme suggested by Anderson et al. (1976). This stratification was required for designing the ovitrapping survey and for classifying satellite imagery to create a landcover map.

Egg survey

Mosquito eggs were collected throughout the county by ovitrapping during a 16-wk period from May 29 to September 18, 2000 (Fig. 1). Ovitraps were made using 450-ml black plastic cups with several drain holes punched halfway down the sides. The inside of each cup was lined with a 5-cm-wide strip of seed germination paper as an oviposition substrate (Steinly et al. 1991). The cups were filled partially with water before placement at each sampling site. Ovitraps were distributed and collected weekly at representative sites in each of the 6 landcover types at a variety of elevations (range for the study period: 440–1,271 m). Ovitrap sites generally were located within walking distance of roads or other automobile-accessible areas and were distributed throughout the county during each sampling period. The geographic location of each ovitrap site was recorded with a hand-held GPS III Plus receiver (Garmin International, Inc., Olathe, KS) so that trap and egg data could be depicted spatially. During the first 4 wk of the survey, 22 new ovitraps were set out each week (21 during wk 1), with a single ovitrap placed at each sampling site. These ovitraps were sampled repeatedly at 4-wk intervals through the end of the 16-wk period of the study, with the exception of 6 sites from the first week that were continuously sampled weekly throughout the study period. In addition, 6 new sites were set out and collected each week after the first 4 wk in habitats where lower numbers of mosquitoes were expected (shrub and brush rangeland, herbaceous rangeland, and barren land) to obtain an accurate representation of oviposition in these habitats. A total of 160 sites in the 5 landcover types, excluding water, were visited during the study, resulting in 490 ovitrap collections. Eggs collected weekly from ovitraps were identified to species (Linley 1989a, 1989b) and counted.

Statistical analysis

A generalized linear model analysis of variance (GLM ANOVA) was used to test for differences among means of square root-transformed [$\sqrt{(y + 0.1)}$] egg counts in relation to landcover and week of sampling. Fisher's least significant difference (LSD) multiple comparison test (α = 0.05) was used for mean separation. All statistics were calculated in NCSS Statistical Software 2000 (Hintze 1998).

Landcover map

A landcover map of Wise County was developed from Landsat 7 Enhanced Thematic Mapper (ETM+) imagery (path 18: row 34), which was acquired by the satellite on July 3, 2000. The data were classified into 6 predefined landcover types (Anderson et al. 1976) using the TNTmips map and image processing system (Microimages, Inc., Lincoln, NE) and the classification method described by Brewster et al. (1999). Six of the seven Landsat ETM+ spectral bands were used in the classification: blue, green, red, near-infrared, and 2 mid-infrared bands. The thermal infrared band was not used because of its coarser spatial resolution (~60 m) compared with that of the other bands (28.5 m). Prior to image classification, the geographic coordinates of representative sites in each of the landcover types were recorded with the GPS receiver. Using landcover descriptions at these sites as a reference, known areas were defined for each landcover type, which then were used as a training dataset for the supervised maximum likelihood classification of the satellite image. The accuracy of the landcover map was evaluated primarily using the error matrix generated by the classifier, which compared pixels of known landcover in the training data with the pixels in landcover classes predicted by the classification (Congalton 1991). The resulting landcover map had a spatial resolution equal to that of the original satellite imagery (28.5 m).

Bayesian classification

A Bayesian decision-rule model was used to classify Wise County into maps of the probability of high abundance of the 2 mosquito species based on the assumption that oviposition activity at each ovitrap site was a good indicator of mosquito abundance at or in close proximity to that site. The combination of remote sensing and Bayesian classification has been applied in studies of other animal species (e.g., Aspinall 1991, Aspinall and Veitch 1993, Hepinstall and Sader 1997, Tucker et al. 1997). In discrete form, the Bayesian model is defined mathematically as,

$$P(M_{\text{high}}|H) = \frac{P(M_{\text{high}}) \times P(H|M_{\text{high}})}{P(M_{\text{high}}) \times P(H|M_{\text{high}}) + P(M_{\text{low}}) \times P(H|M_{\text{low}})}, \quad (1)$$

where H represents habitat type, $P(M_{\text{high}})$ is the prior probability of high oviposition activity, $P(M_{\text{low}})$ is the prior probability of low oviposition activity, $P(H \mid M_{\text{high}})$ is the conditional probability of finding a specific habitat given high oviposition activity, $P(H \mid M_{\text{low}})$ is the conditional probability of finding a specific habitat given low oviposition activity, and $P(M_{\text{high}} \mid H)$ is the posterior probability of high oviposition activity for a particular habitat. Actual high or low oviposition activity was defined by whether the count for a particular trap was above or below the seasonal mean number of eggs collected for the individual species. As such, the prior probabilities of high and low oviposition activity for each species were calculated by dividing the number of sites with egg numbers above and below the seasonal mean, respectively, by the total number of collections during the period of interest. Conditional probabilities were calculated by dividing the total number of sites above and below the threshold in each habitat by the total number of sites that were above and below the threshold for all habitats. Prior and conditional probabilities were calculated for each 28.5-m pixel in the landcover map to create maps of these variables that were entered into equation 1 to produce a map of the posterior probabilities for high mosquito oviposition activity for the entire county.

The accuracy of the predictions was tested by creating a buffer zone of 200 m around each ovitrap location and comparing the average of posterior probabilities for high oviposition activity within the zone with the actual oviposition at the location. The radius of 200 m was chosen because it encompassed the flight range for most *Oc. triseriatus* (Mather and DeFoliart 1984) and *Ae. albopictus* (Bonnet and Worcester 1946, Hawley 1988, Niebylski and Craig 1994). The numbers of occurrences of actual high and low oviposition activity, defined by the seasonal mean threshold described earlier, and the numbers of occurrences of predicted high and low oviposition activity, defined by average posterior probabilities ≥50% or <50%, respectively, were entered into error matrices (Fielding and Bell 1997) to derive metrics that explained the agreement between model predictions and the ovitrap data (Table 1).

RESULTS

Ovitrapping survey

The number of eggs collected during the study was higher for *Oc. triseriatus* (62,340 eggs) than *Ae. albopictus* (11,291 eggs). *Oclerotatus triseriatus* had a seasonal mean of 20.4 eggs/trap-day, with highest oviposition activity in late June (35.8 eggs/trap-day; Fig. 2) and several smaller peaks occurring throughout the remainder of the season, although variation among weeks was not significant ($F = 0.60$, df = 15, $P = 0.874$; Fig. 2). *Aedes albopictus* had a seasonal mean of 3.7 eggs/trap-day, with significant variation in oviposition activity over time ($F = 6.37$, df = 15, $P < 0.001$). Num-

Table 1. Error matrix and accuracy measures used for assessing predictive capabilities of the Bayesian model.

Error matrix[1]				Measure[2]	Calculation[3]
				Accuracy	$(a + d)/N$
		Actual		Kappa (K)	$\dfrac{(a + d) - (((a + c)(a + b) + (b + d)(c + d))/N)}{N - (((a + c)(a + b) + (b + d)(c + d))/N)}$
		High	Low		
Predicted	High	a	b	Prevalence	$a/(a + b + c + d)$
	Low	c	d	False-positive rate	$b/(b + d)$
				False-negative rate	$c/(a + c)$

[1] Adapted from Fielding and Bell (1997).

[2] Accuracy is the proportion of sites that are classified correctly as having high or low oviposition activity. K is a more comprehensive measure of prediction success.

[3] N is the total number of evaluated sites.

bers of *Ae. albopictus* eggs collected were low during June (<1.0 egg/trap-day), increased during July, and peaked in late August (8.9 eggs/trap-day; Fig. 2).

Oviposition preferences for both species differed significantly among the 5 landcover types for the collection season (*Oc. triseriatus:* $F = 54.38$, $df = 4$, $P < 0.001$; *Ae. albopictus:* $F = 27.61$, $df = 4$, $P < 0.001$; Fig. 3). Oviposition activity for *Oc. triseriatus* was significantly higher in forested than in urban/residential habitats. Activity in shrub and brush rangeland, herbaceous rangeland, and barren land did not differ significantly, but the numbers of eggs were significantly lower than in forested and urban/residential sites (Table 2; Fig. 3A). In contrast, the mean numbers of *Ae. albopictus* eggs were significantly higher in urban areas than in all other habitats (Table 2), although relative oviposition activity of *Ae. albopictus* among landcover classes varied over time ($F = 1.75$, $df = 60$, $P = 0.001$; Fig. 3B) and oviposition in particular weeks sometimes was higher in other habitat types (Fig. 3B). *Aedes albopictus* had approximately equal oviposition preference for barren land, shrub and brush rangeland, and herbaceous rangeland, with the lowest activity occurring in forested habitats (Table 2).

Landcover classification

Figure 4 shows the landcover map that was developed from the satellite imagery of Wise County. Of 22,303 pixels in the training dataset that was used to develop the landcover map of Wise County, 98.1% were classified correctly, and Kappa (K, an indicator of prediction success above that expected by chance) was 0.95. Commission errors, the uncertainties in the association of pixels on the landcover map with classes on the ground, ranged from 0.0 to 9.7%. From the map, it was estimated that ~63.2% of the landscape in the county is forested, 18.0% is urban/residential, 10.6% is shrub and brush rangeland, 4.9% is herbaceous rangeland,

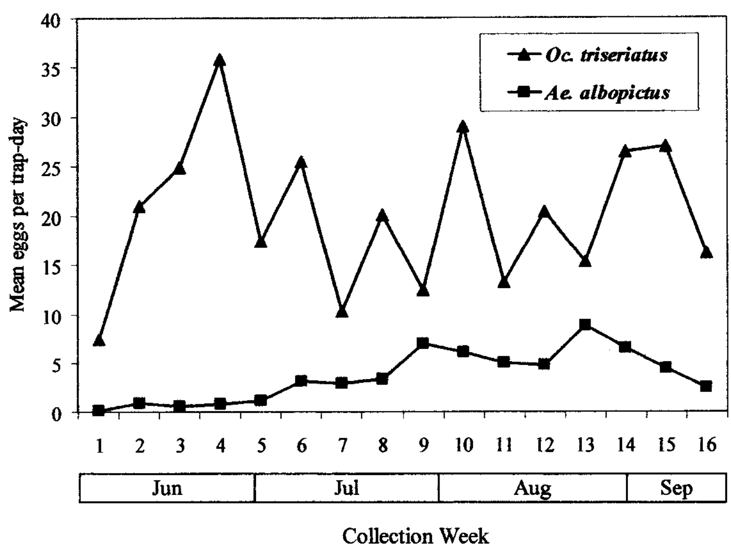

Fig. 2. Mean eggs per trap-day from all ovitrap sites for *Ochlerotatus triseriatus* and *Aedes albopictus*. Eggs were collected weekly between May 29 and September 18, 2000.

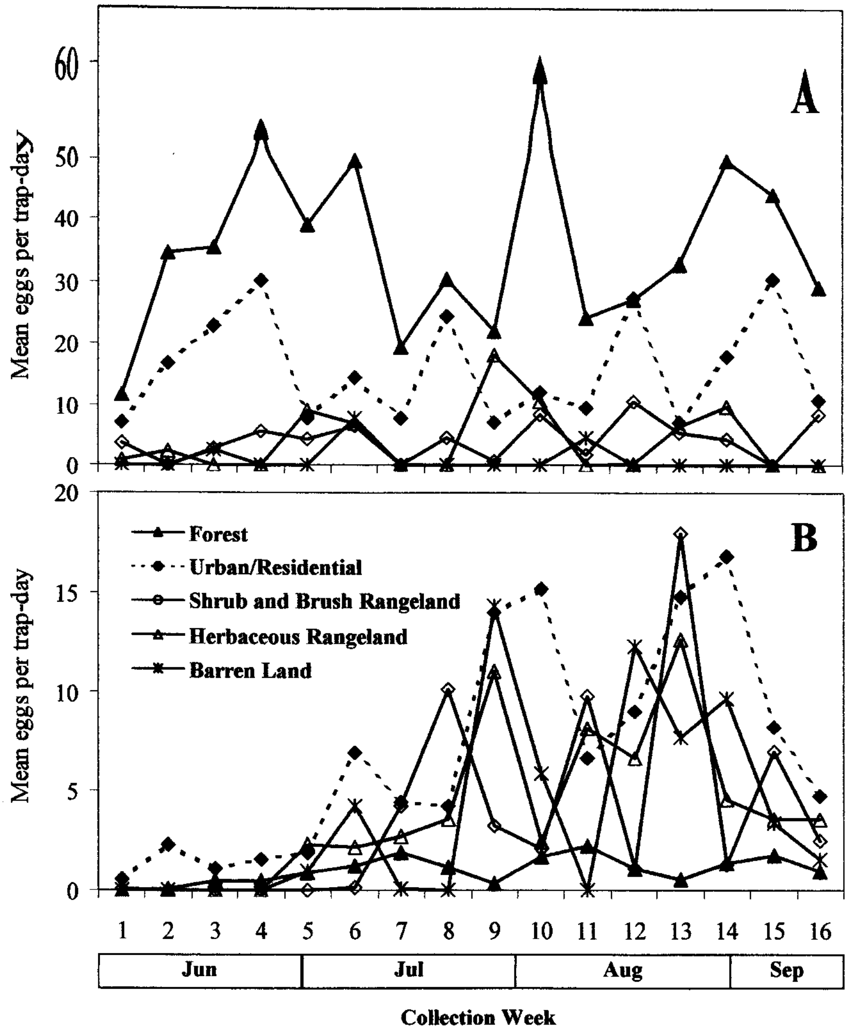

Fig. 3. Mean eggs per trap-day for *Ochlerotatus triseriatus* (A) and *Aedes albopictus* (B) by landcover type in Wise County. Eggs were collected weekly between May 29 and September 18, 2000.

3.1% is barren land, and 0.2% is water. Because of the 28.5-m resolution of the Landsat ETM+ imagery, areas classified in the water landcover type represented large bodies of water such as lakes, which were not considered suitable habitats for the treehole and container-breeding mosquito species and were not sampled in this study.

Bayesian classification

Maps of the posterior probabilities of high oviposition activity for both *Oc. triseriatus* and *Ae. albopictus* were created for each of the eight 2-wk periods during the 16-wk collection season (e.g., Fig. 5). The maps reflected the fluctuations in ovi-

Table 2. Mean (±SE) eggs per trap-day for *Ochlerotatus triseriatus* and *Aedes albopictus* collected weekly in ovitraps placed in 5 landcover types in Wise County, VA, between May 29 and September 18, 2000.[1]

Landcover	*n*	*Oc. triseriatus*	*Ae. albopictus*
Forest	200	35.51 ± 2.36a	1.03 ± 0.21c
Urban/residential	141	16.72 ± 1.80b	6.84 ± 0.81a
Herbaceous rangeland	60	4.66 ± 1.60c	4.35 ± 0.78b
Shrub and brush rangeland	56	4.32 ± 0.96c	4.23 ± 1.07b
Barren land	33	0.81 ± 0.54c	4.34 ± 1.32b

[1] Means within a column followed by the same letter are not significantly different ($P > 0.05$) when analyzed by GLM (ANOVA) and Fisher's LSD multiple comparison tests.

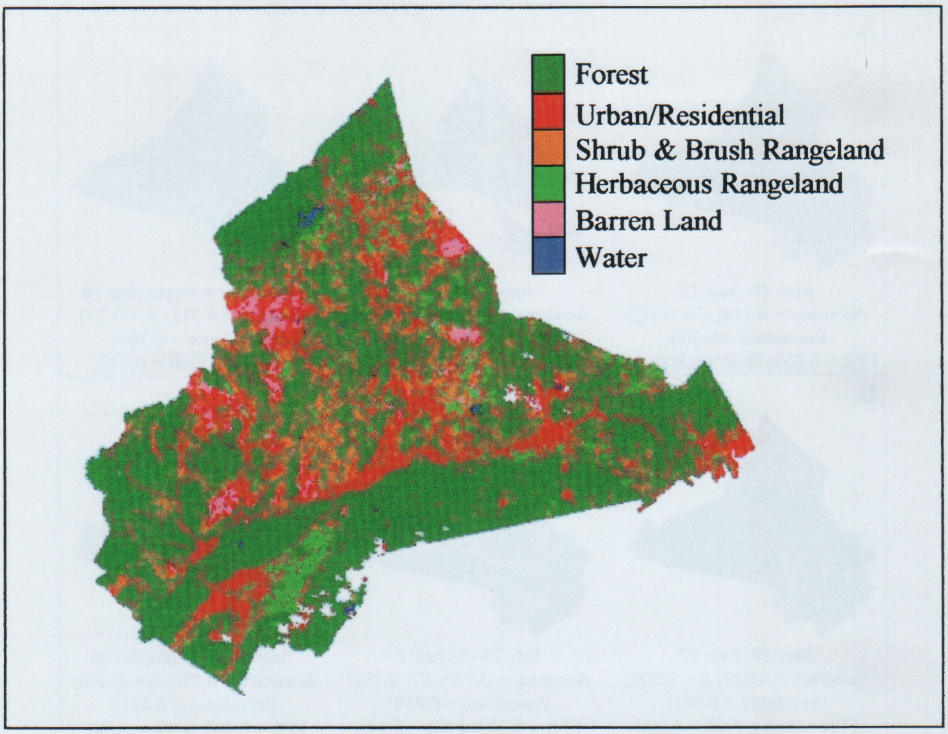

Fig. 4. Landcover map of Wise County, VA, showing six broad landcover types. Map was developed from a Landsat 7 ETM+ image (path 18: row 34) acquired on June 03, 2000. White areas within the county's perimeter represent areas obscured by cloud cover at the time of image acquisition.

position activity and the occurrence patterns of both species. The seasonal means of 20.4 and 3.7 eggs/trap-day for *Oc. triseriatus* and *Ae. albopictus,* respectively, were used as thresholds for defining actual high and low oviposition activity levels. These actual levels were compared with the levels predicted by the Bayesian model for each ovitrapping site. County-wide oviposition activity for *Oc. triseriatus* was predicted with overall accuracy levels ranging from 55 to 79%, with the highest probabilities for high oviposition activity in forested areas. False-negative rates for the predictions were between 0.42 and 1.00. Urban areas had the highest predicted oviposition activity for *Ae. albopictus* during most weeks. The accuracy of the predictions for *Ae. albopictus* generally was higher (70–94%) than for *Oc. triseriatus*, with very high accuracy levels early in the season and lower levels later in the season as oviposition activity increased. False-negative rates for these predictions ranged from 0.26 to 1.00. The levels of K, as defined by Landis and Koch (1977), varied from poor ($K < 0.4$) to good ($0.4 < K < 0.75$) for both species.

DISCUSSION

This study showed that *Oc. triseriatus* and *Ae. albopictus,* newly sympatric mosquito species in southwestern Virginia, are using different primary habitat types for oviposition, with some overlap in intermediate habitats. The highest numbers of *Oc. triseriatus* eggs were collected in forested habitats, while the highest numbers of *Ae. albopictus* eggs were collected in urban and residential areas. A previous season-long evaluation of *Oc. triseriatus* oviposition preferences at a single La Crosse encephalitis human case site in Wise County revealed that *Oc. triseriatus* deposited eggs equally in ovitraps placed in the yard and surrounding forested areas (Barker et al. 2003). However, the more extensive county-wide survey in this study found that *Oc. triseriatus* prefers forested areas over urban and residential habitats for oviposition. Because the earlier study was conducted at a single site with a low number of traps placed in each habitat type, the present study provides a better indication of overall oviposition preferences for the species throughout the area. In shrub and brush rangeland, herbaceous rangeland, and barren land, the numbers for both species were lower than in their respective preferred habitats, indicating that their use of these habitats is relatively infrequent, at least for oviposition.

The oviposition preference of *Ae. albopictus* for urban and residential areas in Wise County should be qualified by a description of the urban areas that exist there. Areas defined as urban/residential for the purposes of the study were simply places of

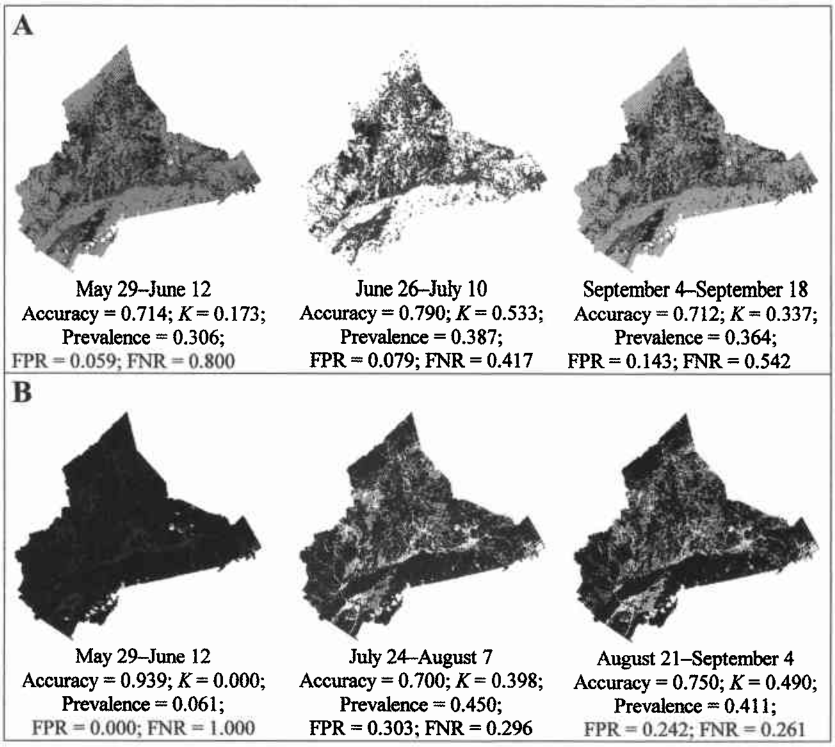

Fig. 5. Selected maps of Wise County showing posterior probabilities of high oviposition activity from the Bayesian model for *Ochlerotatus triseriatus* (A) and *Aedes albopictus* (B). Grayscale levels from black to white represent the range of probabilities (0–80%) of high oviposition activity. K = Kappa, FPR = false-positive rate, and FNR = false-negative rate.

human habitation, usually a house with a manicured lawn within a residential area or rural housing cluster or a business district within a small town. Large cities are not found in Wise County, so areas classified as urban/residential are similar to suburban areas near major cities where trees and other vegetation are interspersed among the houses and other buildings. Nevertheless, the preference of *Ae. albopictus* for urban areas and the relatively low abundance found in forests agree well with the proposed origin of this species in the USA from used tire shipments from northern Asia (Hawley et al. 1987). Studies of macrohabitat preferences of *Ae. albopictus* in Japan showed that this mosquito is a common or regularly occurring species in urban, suburban, and rural areas but is rare in forest (Hawley 1988). However, studies in other parts of Asia found that *Ae. albopictus* was common in forests (Hawley 1988), which led Mogi (1982) to suggest that forest-dwelling populations of *Ae. albopictus* in some areas of Asia may have resulted from readaptation of anthropophilic strains of the species to the forest habitat. Thus, it is possible that, because of the predominance of forest in Wise County, *Ae. albopictus* populations eventually may adapt to use forested habitats more frequently and compete for resources more directly with native *Oc. triseriatus*.

Aside from habitat-related variation in oviposition intensity, another factor that influences oviposition activity in an individual trap is competition from other oviposition containers. In an effort to minimize this source of variation, sites with anomalously high numbers of competing oviposition sites, such as tire dumps, were avoided because of the problem of competing oviposition containers and because such sites generally were not representative of the broad landcover classes used in the study. It was impossible to equalize the numbers of competing oviposition sites in all habitat types, such as treeholes in forested areas and peridomestic containers in urban areas, and some variation in oviposition intensity within and among habitat types undoubtedly resulted from these differences. However, because the highest numbers of eggs for both species were collected in habitat types that presumably also had the highest numbers of competing ovitrap sites (treeholes for *Oc. triseriatus* and peridomestic containers for *Ae. albopictus*) and because lower levels of oviposition activity were observed in habitat types with the fewest competing oviposition sites (barren land, herbaceous rangeland, and shrub and brush rangeland), equalizing the number of competing oviposition sites among habitat types is likely to have the effect of increasing the observed differences between preferred and alternative habitats without appreciably changing the relative preference for individual habitat types.

For the Bayesian modeling portion of the study, it was assumed that oviposition activity at an ovitrap site was correlated positively with the abundance of female *Oc. triseriatus* and *Ae. albopictus* at that site. Although adult mosquitoes were not collected in this study, females of *Oc. triseriatus* and *Ae. albopictus* are known to remain close to their larval sites, (Horsfall 1955) and because their flight range is low (Bonnet and Worcester 1946, Mather and DeFoliart 1984, Hawley 1988, Niebylski and Craig 1994), activities such as host-seeking and resting would be expected to take place within a short distance of sites used for oviposition. Further studies incorporating adult collections in the various habitat types along with ovitrapping would provide greater insight into differential habitat usage patterns.

The Bayesian model was moderately successful in predicting the occurrence of high oviposition activity for *Oc. triseriatus* and *Ae. albopictus* throughout Wise County. Kappa (K), which takes into account both correct and incorrect predictions, provides a measure of prediction success of the model above that expected by chance (Fielding and Bell 1997). K was highest for both species during periods of peak oviposition activity, suggesting that the predictive power of the model was highest during periods when LAC transmission risk also was likely to be high. Overall accuracy levels, particularly for *Ae. albopictus,* were very high (>90%) during the early season, but accuracy levels are dependent on prevalence (proportion of sites that has actual high oviposition levels). Thus, during the early season, when oviposition rates are low, very high accuracy levels can be achieved even with a poor predictor if nearly all sites have low actual and predicted oviposition activity (Fig. 5B). Rates for false negatives were lowest during periods of peak abundance for both species, while rates for false positives were highest during these periods. False-positive and false-negative rates are measures of the proportion of actual low or high abundance sites, respectively, that were not predicted as such. For prediction of disease-vector abundance, false-negative rates must be minimized because false negatives result in neglect of areas with high disease risk by public health and vector-control personnel. Decisions based on false-positive predictions may result in wasted resources, but not in increased risk of human disease.

An advantage of using Bayesian models is that prior probabilities can be estimated subjectively or based on user-defined thresholds (e.g., the thresholds for high and low oviposition activity used in this study). These models also can be updated easily based on new information. The posterior probability of high oviposition activity, for example, can be used to derive the prior probabilities of high and low oviposition activity in the next iteration of the model when new information is acquired. Despite these advantages, there were several factors that could account for the moderate success of the model in this study. The ovitrap data were not extensive enough to allow partitioning for prediction and validation, and a suitable retrospective mosquito abundance dataset was not available for the study area. Validation of model predictions based on data used to create a model generally is considered questionable or even invalid, but in this study, the input probabilities for the model were calculated independently of the spatial arrangement of the data and the assessment was based on the locations of individual sites and their surrounding landcover. Therefore, although the evaluations of predictions may not be as robust as they would have been if they had been tested with an independent dataset, the current assessment still provides a reasonable depiction of the utility of the Bayesian model. The moderate levels of accuracy achieved also suggest a need to consider additional ecologically relevant factors. Elevation was considered, but no relationship to mosquito oviposition during the study period was found, agreeing with a study conducted by Ballard et al. (1987) in woodlands of eastern Kentucky. Rainfall also was considered, but no significant correlation between this variable and oviposition activity was found at varying lag periods (0–6 wk) to account for the generation time from egg hatching to oviposition by female mosquitoes. The lack of correlation might have resulted from the coarse spatial resolution of the rainfall data that were available from weather stations scattered throughout Wise County. Because rainfall can vary dramatically, even over short distances, a better estimate of rainfall might have been obtained by placing a rain gauge at each ovitrapping site. Rainfall was relatively frequent during the collection period, with measurable rainfall recorded during 90 of 183 days from April through September 2003 in Wise, VA (National Oceanic and Atmospheric Administration 2003), so it might be more closely correlated with mosquito abundance during years when it is more sporadic and serves to limit mosquito production.

In conclusion, the study showed that *Oc. triseriatus* and *Ae. albopictus* in southwestern Virginia have a clear oviposition preference for different habitats. Spatially referenced ground surveys and predictive modeling using data on oviposition activity as an indicator of mosquito abundance could provide timely predictions of vector abundance over broad areas. Because vector abundance is related to risk for virus transmission to humans, particularly for a vertically transmitted virus such as LAC (Watts et al. 1973b, Miller et al. 1977), predictions of vector abundance could be useful for targeting public awareness campaigns and vector-control measures in areas with the greatest risk for virus transmission to humans. These approaches, along with vertebrate serosurveys and virus testing of mosquitoes, would provide a better understanding of LAC distribution within the county that would improve the assessment of disease risk associated with predicted mosquito distributions.

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